```
#google colab
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.metrics import r2_score
import statsmodels.api as sm
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarnir
  import pandas.util.testing as tm
```

```
s=pd.read_csv("student.csv")
s
```

	Unnamed: 0	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	F
0	1	GP	F	18	U	GT3	A	4	4	at_home	tea
1	2	GP	F	17	U	GT3	T	1	1	at_home	c
2	3	GP	F	15	U	LE3	T	1	1	at_home	c
3	4	GP	F	15	U	GT3	T	4	2	health	serv
4	5	GP	F	16	U	GT3	T	3	3	other	c
...	...	...	...	...	...	...	...	...	...	...	
390	391	MS	M	20	U	LE3	A	2	2	services	serv
391	392	MS	M	17	U	LE3	T	3	1	services	serv
392	393	MS	M	21	R	GT3	T	1	1	other	c
393	394	MS	M	18	R	LE3	T	3	2	services	c
394	395	MS	M	19	U	LE3	T	1	1	other	at_h

395 rows × 34 columns

```
s.isna().sum()
```

```
Unnamed: 0    0
school        0
sex           0
age           0
address       0
famsize       0
Pstatus       0
Medu          0
Fedu          0
```

```
Mjob          0
Fjob          0
reason        0
guardian      0
traveltime    0
studytime     0
failures      0
schoolsup     0
famsup        0
paid          0
activities    0
nursery       0
higher        0
internet      0
romantic      0
famrel        0
freetime      0
goout         0
Dalc          0
Walc          0
health        0
absences      0
G1            0
G2            0
G3            0
dtype: int64
```

```
s.dtypes
```

```
Unnamed: 0     int64
school        object
sex           object
age            int64
address       object
famsize       object
Pstatus       object
Medu           int64
Fedu           int64
Mjob          object
Fjob          object
reason        object
guardian      object
traveltime     int64
studytime      int64
failures       int64
schoolsup     object
famsup        object
paid          object
activities    object
nursery       object
higher        object
internet      object
romantic      object
famrel         int64
freetime       int64
goout          int64
Dalc           int64
Walc           int64
health         int64
absences       int64
```

```
G1            int64
G2            int64
G3            int64
dtype: object
```

```
s._get_numeric_data()
```

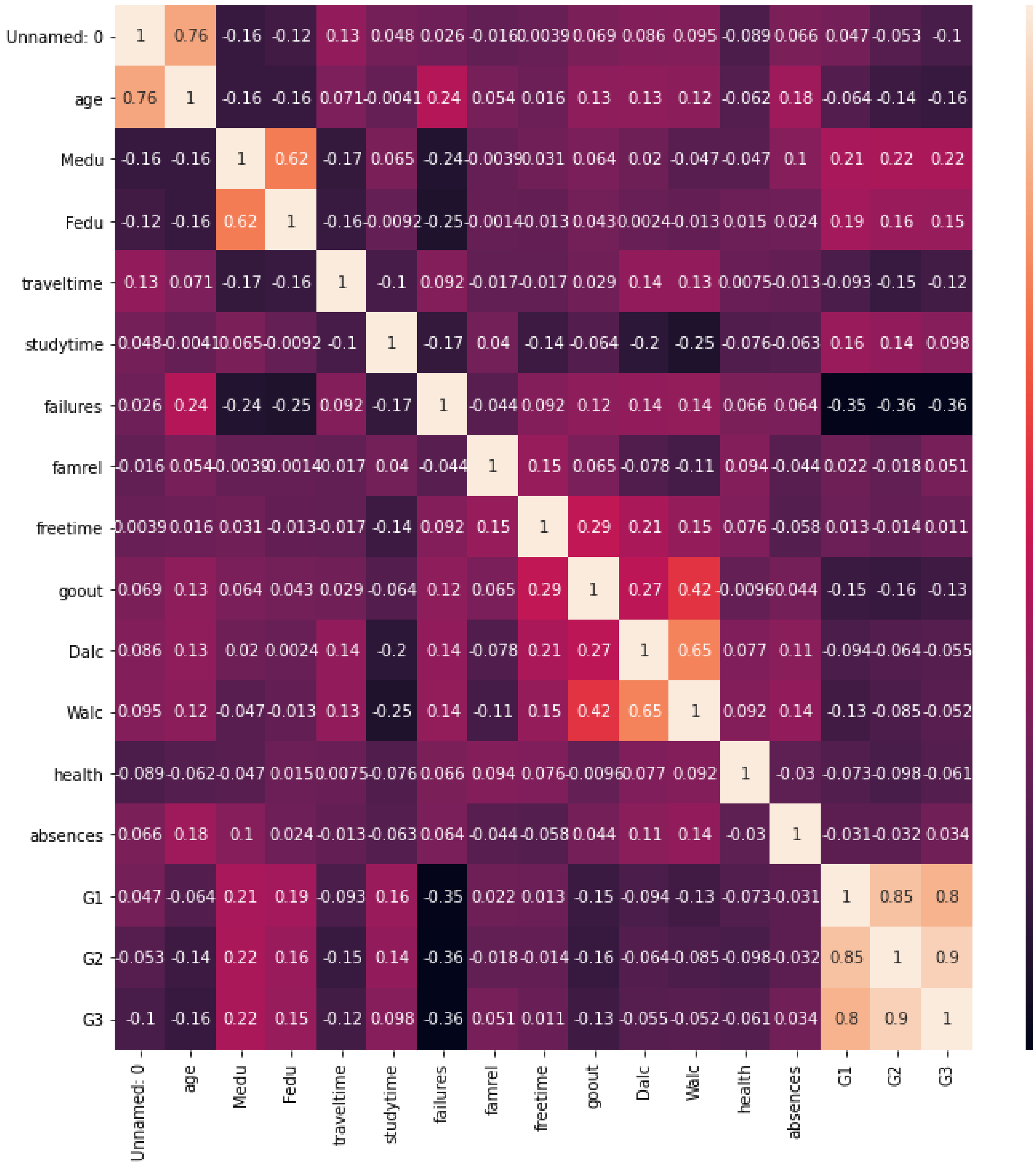
	Unnamed: 0	age	Medu	Fedu	traveltime	studytime	failures	famrel	freetime	go
0	1	18	4	4	2	2	0	4	3	
1	2	17	1	1	1	2	0	5	3	
2	3	15	1	1	1	2	3	4	3	
3	4	15	4	2	1	3	0	3	2	
4	5	16	3	3	1	2	0	4	3	
...	...	...	...	...	...	...	...	...	...	
390	391	20	2	2	1	2	2	5	5	
391	392	17	3	1	2	1	0	2	4	
392	393	21	1	1	1	1	3	5	5	
393	394	18	3	2	3	1	0	4	4	
394	395	19	1	1	1	1	0	3	2	

395 rows × 17 columns

```
categorical=[i for i in s.columns if s.dtypes[i]=='object']
categorical
```

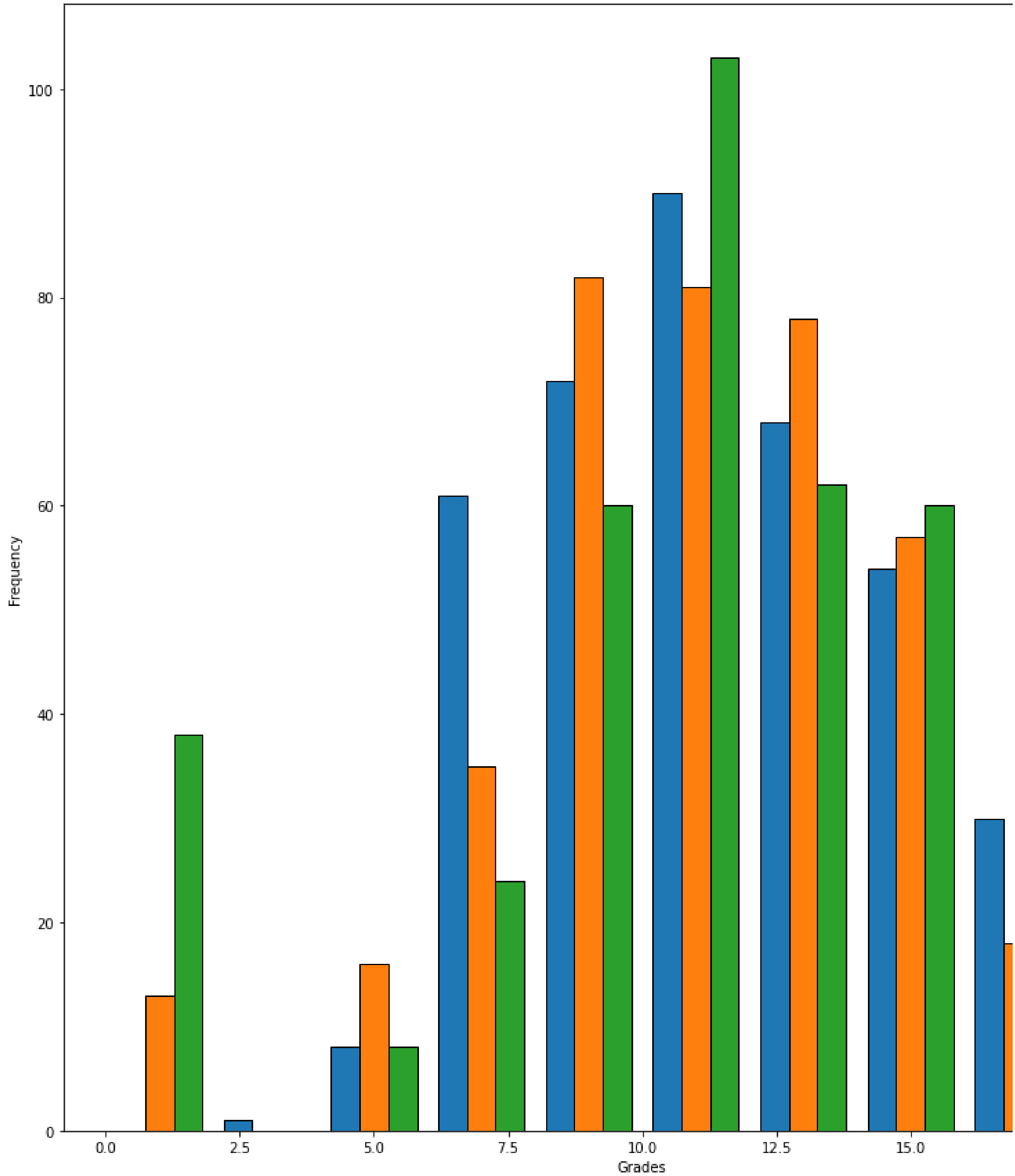
```
['school',
 'sex',
 'address',
 'famsize',
 'Pstatus',
 'Mjob',
 'Fjob',
 'reason',
 'guardian',
 'schoolsup',
 'famsup',
 'paid',
 'activities',
 'nursery',
 'higher',
 'internet',
 'romantic']
```

```
#correlation before converting any categorical data
plt. figure(figsize=(12,12))
sn.heatmap(s.corr(),annot=True)
plt.show()
```




```
plt.figure(figsize=(15,15))
plt.hist([s['G1'],s['G2'],s['G3']],edgecolor='black',histtype='bar')
# plt.hist(df2['B'],edgecolor='black',histtype='bar')
# plt.hist(df3['C'],edgecolor='black',histtype='bar')
plt.legend(['G1','G2','G3'])
plt.xlabel("Grades")
plt.ylabel("Frequency")
```

```
Text(0, 0.5, 'Frequency')
```




```
s1=s.copy()
```

```
#dropping Mjob', 'Fjob', 'reason','guardian' coz grades wouldnt depend on them.
s1=s1.drop(['Mjob','Fjob','reason','guardian'],axis=1)
s1
```

	Unnamed: 0	school	sex	age	address	famsize	Pstatus	Medu	Fedu	traveltime	s
0	1	GP	F	18	U	GT3	A	4	4	2	
1	2	GP	F	17	U	GT3	T	1	1	1	
2	3	GP	F	15	U	LE3	T	1	1	1	
3	4	GP	F	15	U	GT3	T	4	2	1	
4	5	GP	F	16	U	GT3	T	3	3	1	
...	...	...	...	...	...	...	...	...	...	...	
390	391	MS	M	20	U	LE3	A	2	2	1	
391	392	MS	M	17	U	LE3	T	3	1	2	
392	393	MS	M	21	R	GT3	T	1	1	1	

```
# Converting Categorical Variable 'school' into Numerical Variables.
type_mapping = {"GP": 0, "MS": 1}
s1['school']= s1['school'].map(type_mapping)

# Converting Categorical Variable 'sex' into Numerical Variables.
type_mapping = {"F": 0, "M": 1}
s1['sex'] = s1['sex'].map(type_mapping)

# Converting Categorical Variable 'address' into Numerical Variables.
type_mapping = {"R": 0, "U": 1}
s1['address'] = s1['address'].map(type_mapping)

# Converting Categorical Variable 'famsize' into Numerical Variables.
type_mapping = {"LE3": 0, "GT3": 1}
s1['famsize'] = s1['famsize'].map(type_mapping)

# Converting Categorical Variable 'Pstatus' into Numerical Variables.
type_mapping = {"T": 0, "A": 1}
s1['Pstatus'] = s1['Pstatus'].map(type_mapping)

# Converting Categorical Variable 'schoolsup' into Numerical Variables.
type_mapping = {"no": 0, "yes": 1}
s1['schoolsup'] = s1['schoolsup'].map(type_mapping)

# Converting Categorical Variable 'famsup' into Numerical Variables.
type_mapping = {"no": 0, "yes": 1}
s1['famsup'] = s1['famsup'].map(type_mapping)

# Converting Categorical Variable 'paid' into Numerical Variables.
type_mapping = {"no": 0, "yes": 1}
s1['paid'] = s1['paid'].map(type_mapping)

# Converting Categorical Variable 'activities' into Numerical Variables.
type_mapping = {"no": 0, "yes": 1}
s1['activities'] = s1['activities'].map(type_mapping)

# Converting Categorical Variable 'nursery' into Numerical Variables.
```

```
type_mapping = {"no": 0, "yes": 1}
s1['nursery'] = s1['nursery'].map(type_mapping)

# Converting Categorical Variable 'higher' into Numerical Variables.
type_mapping = {"no": 0, "yes": 1}
s1['higher'] = s1['higher'].map(type_mapping)

# Converting Categorical Variable 'internet' into Numerical Variables.
type_mapping = {"no": 0, "yes": 1}
s1['internet'] = s1['internet'].map(type_mapping)

# Converting Categorical Variable 'romantic' into Numerical Variables.
type_mapping = {"no": 0, "yes": 1}
s1['romantic'] = s1['romantic'].map(type_mapping)


#correlation after converting some categorical variables to numerical
plt. figure(figsize=(20,20))
sn.heatmap(s1.corr(),annot=True)
plt.show()
```

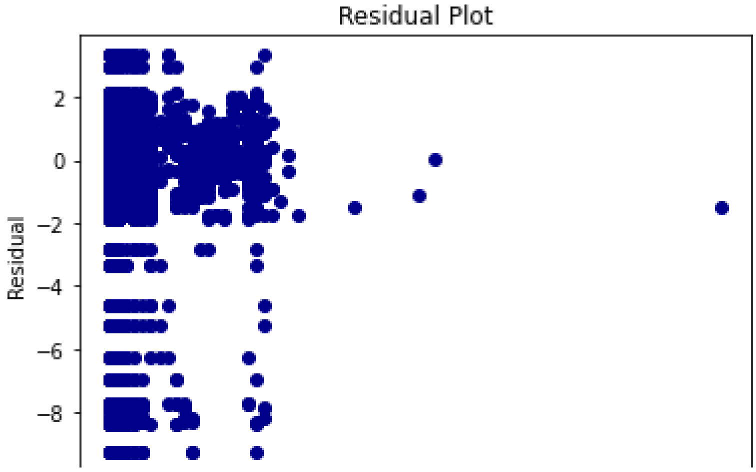

```
#splitting data
train_data = s1[:int(0.7*(len(s1)))]
test_data = s1[int(0.7*(len(s1))):]
```

```
Xtrain=train_data.drop(["G3","Unnamed: 0"],axis=1)
Ytrain=train_data["G3"]
Xtest=test_data.drop(["G3","Unnamed: 0"],axis=1)
Ytest=test_data["G3"]
```

```
model=LinearRegression(fit_intercept = True, normalize = True)
model.fit(Xtrain,Ytrain)
Ypred = model.predict(Xtest)


residuals = Ytest-Ypred
plt.plot(Xtest,residuals, 'o', color='darkblue')
plt.title("Residual Plot")
plt.xlabel("Independent Variable")
plt.ylabel("Residual")
#as the residual plot isnt random, we might have autocorrelation between independent varia
```

```
Text(0, 0.5, 'Residual')
```




```
print("Mean Absolute Error:", metrics.mean_absolute_error(Ytest, Ypred))
print("Mean Squared Error:", metrics.mean_squared_error(Ytest, Ypred))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(Ytest, Ypred)))
print("R Squared Score is:", r2_score(Ytest, Ypred))
```

```
Mean Absolute Error: 1.3995022209609316
Mean Squared Error: 6.113160445501219
Root Mean Squared Error: 2.4724806259101846
R Squared Score is: 0.7108891391352146
```

```
#To find which independent variables actual help in predicting G3
X2 = sm.add_constant(Xtrain)
model_stats = sm.OLS(Ytrain.values.reshape(-1,1), X2).fit()
model_stats.summary()
```

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.885
Model:	OLS	**Adj. R-squared:**	0.872
Method:	Least Squares	**F-statistic:**	70.68
Date:	Fri, 02 Jul 2021	**Prob (F-statistic):**	1.24e-100
Time:	11:44:44	**Log-Likelihood:**	-512.29
No. Observations:	276	**AIC:**	1081.
Df Residuals:	248	**BIC:**	1182.
Df Model:	27		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-3.9205	2.271	-1.726	0.086	-8.393	0.552
school	2.959e-15	2.86e-15	1.034	0.302	-2.68e-15	8.59e-15
sex	-0.0003	0.232	-0.001	0.999	-0.456	0.456
age	0.0554	0.111	0.499	0.618	-0.163	0.274
address	0.0067	0.283	0.024	0.981	-0.551	0.564
famsize	0.2050	0.232	0.882	0.379	-0.253	0.663
Pstatus	0.5824	0.345	1.688	0.093	-0.097	1.262
Medu	0.1894	0.127	1.494	0.137	-0.060	0.439
Fedu	-0.2049	0.123	-1.664	0.097	-0.448	0.038
traveltime	0.1205	0.157	0.769	0.443	-0.188	0.429
studytime	-0.2030	0.134	-1.512	0.132	-0.467	0.061
failures	-0.2442	0.153	-1.595	0.112	-0.546	0.057
schoolsup	0.2299	0.289	0.796	0.427	-0.339	0.799
famsup	0.1725	0.227	0.759	0.448	-0.275	0.620
paid	0.1168	0.225	0.519	0.604	-0.326	0.560
activities	-0.0769	0.212	-0.362	0.717	-0.495	0.341
nursery	-0.2337	0.266	-0.879	0.380	-0.757	0.290
higher	0.8581	0.527	1.628	0.105	-0.180	1.896
internet	-0.3282	0.290	-1.131	0.259	-0.900	0.243
romantic	-0.2209	0.230	-0.961	0.338	-0.674	0.232
famrel	0.3764	0.116	3.248	0.001	0.148	0.605
freetime	0.0327	0.111	0.296	0.768	-0.185	0.251
goout	-0.1483	0.104	-1.423	0.156	-0.353	0.057
Dalc	-0.1902	0.154	-1.236	0.218	-0.493	0.113
Walc	0.2463	0.114	2.155	0.032	0.021	0.471
health	0.0147	0.074	0.199	0.843	-0.131	0.161
absences	0.0238	0.016	1.533	0.126	-0.007	0.054
G1	0.1244	0.059	2.104	0.036	0.008	0.241
G2	0.9617	0.049	19.600	0.000	0.865	1.058

Omnibus:	160.141	**Durbin-Watson:**	1.996
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1193.949
Skew:	-2.284	**Prob(JB):**	5.46e-260
Kurtosis:	12.108	**Cond. No.**	1.01e+16

✓ 0s completed at 5:14 PM